A Practical, Objective and Robust Technique to Directly Estimate Catchment Response Time

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Key points:

1) The median catchment response time (Tr) computed with the proposed method matches the median Tr computed with the traditional method.

2) When using the proposed method, the Tr computed using the multi-event time series is very similar to the median Tr for individual events.

3) The proposed methodology gives robust results for relatively short records and works also in presence of noise and bias in the time series.

Abstract

Methodologies to estimate the response time of a catchment to new rainfall inputs based on rainfall and streamflow observations require the analyst to make a number of uncertain and subjective steps. Moreover, these methods make the assumption that the water producing the discharge peak fell in the last rainfall event, which does not necessary apply to all the environments and conditions. Hence, here we present a practical, objective, and robust method to estimate catchment response time (Tr) based on hourly rainfall and streamflow time series only, which removes most of the sources of uncertainties arising from current methodologies by restating the conceptual hypothesis and minimizing the user's choices. The proposed method, used originally in the field of economics to assess the temporal correlation between two variables, has been adapted to be used for the first time in the field of hydrology. The method does not make any assumption about the rainfall-runoff transformation (no hydrograph separation needed), does not require event selection or parameter estimation, and it is easily reproducible. The above features make the proposed method a useful tool even under different hypothesis regarding the hydrograph water age. The method agrees well with the traditionally used method to estimate Tr from observed hyetographs and hydrographs (Spearman rank correlation r=0.82). The proposed method gives robust results for relatively short records, and works in presence of noise and bias in the time series.

Plain language summary

Methodologies to estimate the time delay of the transformation of rainfall into river discharge based on rainfall and discharge records require a number of highly subjective and uncertain steps. Moreover, the assumptions behind these methods have been proven incorrect, at least in some environments. For this reason, we present a different method which removes those incorrect assumptions and most of the sources of uncertainties arising from the other methodologies. Unlike existing methods, the proposed methodology does not make any assumption about the processes that transform rainfall into river discharge, does not require event identification or parameter estimation and is easily reproducible. We demonstrate that the new approach compares well with the traditionally used method and also works for short and noisy records.

1.Introduction

The need for a new method

The fast response time of a catchment to new rainfall inputs is one of the key time variables in hydrology (Kibler, 1982; Almeida et al., 2014) and its correct estimation is essential for hydrological modelling and hydrograph design. Uncertainty in its estimation can cause errors in estimation of peak discharge rate and timing of flood events (Perdikaris et al., 2018).

McCuen (2009) summarised the estimation procedures for determining this response time using rainfall and streamflow observations. These methodologies are straightforward in transferring theoretical knowledge to an estimation procedure, as they estimate a time parameter using a computational definition. Two of the most commonly used definitions when applying these methods are (McCuen, 2009):

1. The time from end of rainfall excess to the inflection point in the hydrograph falling limb;

2.The time from centre of mass of rainfall excess to centre of mass of direct runoff (also called time lag).

The first definition is the most traditionally used when applying these methods, but it has been demonstrated to be highly uncertain (McCuen, 2009) as it involves identifying the precise times of individual features of hyetograph and hydrograph. The second definition, involving centres of mass, is more robust as averaging accounts for the overall behaviour of the rainfall excess and direct runoff (McCuen, 2009). However, since it is the most traditionally applied, in this work we will consider the first definition and will refer to related estimation procedure as "traditional method".

Nevertheless, applying any of these definitions to estimate the response of the catchment to new rainfall input requires the analyst to take a number of highly uncertain and subjective steps:

- Identification of rainfall-streamflow events: there is no recognized and standardized methodology in the literature to automate the selection of rainfall-streamflow events (Norbiato et al., 2009; Merz & Blöschl, 2009; Tarasova et al., 2018; Mei & Anagnostou, 2015) and the chosen strategy has an impact on rainfall (Dunkerley, 2008) and therefore presumably on streamflow statistics at the event scale. Furthermore, the type and the number of the storm events taken into account can affect the response time of a catchment (Grimaldi et al., 2012).
- Separation of the hydrograph into direct runoff and baseflow: many automated methods for hydrograph separation use recursive one-parameter digital filters (e.g. Lyne & Hollick, 1979, Nathan & McMathon, 1990), but these methods require the estimation of a parameter which lacks a physical meaning. Other, more sophisticated hydrograph separation methods usually involve multiple parameters (e.g. two parameter filter by Eckhardt, 2005), which makes parameter estimation more complicated and uncertain.
- Identifying the time of occurrence of hyetograph and hydrograph features: the noise in the signals can make it difficult to automatically identify these features (e.g. inflection points in the hydrograph), especially when the temporal resolution of the data is high.

Furthermore, recently, tracer studies (e.g. McDonnell, 1990; Berghuijs & Allen, 2019; Gallart et al., 2020) have highlighted how in some environments the storm hydrograph mainly consists of water that fell in previous rainfall events. Thus, for some environments there are clear conceptual weaknesses in the methods summarized by McCuen (2009) as they are mainly based on the concept of runoff event made of water falling in the last rainfall event.

To overcome these limitations, we propose a practical, objective, and robust methodology to directly estimate the fast response of the catchment to new rainfall input using rainfall and streamflow observations. The resulting estimates are conceptually similar to the ones produced by the methods summarized by McCuen (2009), but they express the average time delay between centre of mass of total hyetograph and centre of mass of the corresponding total hydrograph. In particular, the proposed methodology improves upon the existing methods with the following advantages: (a) it makes no assumptions on the rainfall-runoff transformation; (b) there is no need of rainfall-streamflow event selection or hydrograph separation; (c) it requires no parameter estimation; and (d) it is easily reproduced.

We will call the time estimated by the traditional method and the proposed method the "catchment response time" (Tr). The following subsection outlines our reasoning for this.

A Note on Definitions and Terminology

The term "time of concentration" (Tc) is frequently used in quantifying the flow response to rainfall events, but it is unsuitable to describe the method presented in this paper. Often, this terminology is stretched to include estimates coming from methods with very different conceptual hypotheses (Grimaldi et al., 2012), but this can generate confusion and murkiness around the concept of Tc.

Tc is historically defined as the time after initiation of steady rainfall when storage is no longer increasing. For example, storage may refer to surface detention storage (e.g. Luce and Cundy, 1994) or to water stored in an equilibrium flow profile (Henderson and Wooding, 1964). Tc can also be associated with the concept of time to equilibrium (the time from the start of rainfall to peak response) in the case of dry initial conditions and steady input rainfall (Eagleson, 1970).

Confusingly, the International Glossary of Hydrology defines Tc as the time for the storm runoff to flow from the most hydraulically distant point in the catchment to the catchment outlet (W.M.O., 1974; Johansson, 1984). As pointed by Beven (2020), this definition is in contradiction with historical one as it assumes that the water moves as individual particles and not as a wave. Beven (2020) also states that we should abandon the glossary definition and that the concept of velocity of water particles should be replaced by the wave celerity concept, given the fact that water moves as a wave.

Being consistent with the historical definition of Tc when using the terminology "time of concentration" is of paramount importance. In fact, the historical Tc concept is used in engineering applications, especially for small drainage areas, as critical duration (duration of the uniform precipitation for which we observe the maximum discharge) (USDA-NRCS, 2010). Calling estimates coming from methods with different conceptual hypotheses "time of concentration" can generate confusion and potentially could lead to substantial errors in the engineering applications.

Nonetheless, the assumption of steady rainfall behind the historical definition of Tc might not apply to the majority of rainfall events in the real world, especially with larger drainage areas. Hence, the time scale retrieved using methods which follow the historical definition may not reflect the most typical response time of the catchment. Instead, simultaneous measurements of catchment rainfall and streamflow provide evidence of the real-world response time.

McCuen (2009) summarised methods for determining a response time for catchments with rainfall and streamflow observations and he called the resulting time estimates "time of concentration". However, the conceptual basis of hyetograph-hydrograph analysis is inconsistent with the historical definition of Tc, and a different term is needed. For this reason we instead use the term "catchment response time", Tr, for the time derived using the traditional method and the method proposed in this paper.

2.Methodology

2.1. DMCA-based correlation-coefficient methodology

The proposed methodology to directly estimate Tr from rainfall and streamflow observations is based on the Detrending Moving-average Cross-correlation Analysis (DMCA). This technique was developed in economics to understand the time scale at which two variables are most strongly correlated (Kristoufek, 2014; Kristoufek, 2015). To the best of our knowledge it has not yet been applied in hydrology. The Tr estimate calculated with the DMCA-based method characterises the time scale of the transformation from a noisy rainfall input to a smoother streamflow output at the catchment outlet.

The strength of the DMCA-based method is to find the timescale at which two time series are linked even when they exhibit different frequency spectra and are nonlinearly related. If we simply used cross correlation by itself, prior smoothing of the rainfall time series would be required to ensure it had a similar frequency to that of the streamflow series. This smoothing would alter the structure of the input rainfall signal, ultimately leading to errors when calculating the timescale of the catchment response.

We adapted the DMCA methodology to extract an average estimate of Tr from rainfall-streamflow time series containing multiple events. Although the hypothesis of quasi-invariant Tr can be verified only for events with high return periods (Dooge, 1973), an invariant estimate of Tr for each catchment is often useful to characterise the catchment and that's what our proposed method does.

In section 2.1.1 we present the analytical formulae and in section 2.1.2 we show the reasoning behind each step. The DMCA-based method can also be applied at event scale by using a time series created by concatenating copies of the same event. This requires a few adjustments which are presented in section 2.1.3.

2.1.1 Step by step guide to DMCA calculations

Here we outline the steps for calculating Tr using mean catchment rainfall and streamflow time series (typically at hourly time step):

I. Construct the cumulative time series of rainfall R_t and streamflow Q_t. The two time series must have the same length T and the same time step:

$$R_t = \sum_{i=1}^{t} r_i \qquad for\ t=1,2,\dots,T \qquad \text{(Eq.1)}$$

$$Q_t = \sum_{i=1}^{t} q_i \qquad for\ t=1,2,\dots,T \qquad \text{(Eq.2)}$$

Where r_i and q_i are the rainfall and the streamflow records respectively at time t and R_t and Q_t are the cumulative time series for time series of length T.

Then, for a single moving-average window length L (where L is in units of time steps and must be odd as we are using centred moving average):

II. Calculate the fluctuations of each cumulative time series compared to its centred moving average (this is the detrending) with window length L, and then compute the mean squared value of those fluctuations ($F_R^2(L)$ for rainfall and $F_Q^2(L)$ for streamflow):

$$F_R^2(L) = \frac{1}{T-L+1} \sum_{t=0.5(L+1)}^{T-0.5(L-1)} (R_t - \widehat{R_{t,L}})^2 \qquad \text{(Eq.3)}$$

$$F_Q^2(L) = \frac{1}{T-L+1}\sum_{t=0.5(L+1)}^{T-0.5(L-1)}(Q_t - \widehat{Q_{t,L}})^2 \quad \text{(Eq.4)}$$

Where $\widehat{R_{t,L}}$ and $\widehat{Q_{t,L}}$ are the centred moving averages of the cumulative rainfall and streamflow respectively with moving average window length L at time t:

$$\widehat{R_{t,L}} = \frac{1}{L}\sum_{t-0.5(L-1)}^{t+0.5(L-1)} R_t \quad \text{(Eq.5)}$$

$$\widehat{Q_{t,L}} = \frac{1}{L}\sum_{t-0.5(L-1)}^{t+0.5(L-1)} Q_t \quad \text{(Eq.6)}$$

III. In the same way, calculate the mean squared value of the bivariate fluctuations:

$$F_{R,Q}^2(L) = \frac{1}{T-L+1}\sum_{t=0.5(L+1)}^{T-0.5(L-1)}(R_t - \widehat{R_{t,L}})(Q_t - \widehat{Q_{t,L}}) \quad \text{(Eq.7)}$$

IV. Finally, the DMCA-based correlation coefficient for a window length L is:

$$\rho_{DMCA}(L) = \frac{F_{R,Q}^2(L)}{F_R(L)F_Q(L)} \qquad \text{with } -1 \leq \rho_{DMCA}(L) \leq 1 \quad \text{(Eq.8)}$$

Tr is estimated as half of $L_{\min}$-1, where $L_{\min}$ is the window length L which gives the minimum value of the DMCA-based correlation coefficient ρ_{DMCA}. We therefore need to test a wide range of window lengths L, from three hours to several days using a two-hour time step (to ensure that L is an odd number) so that we are sure to include the window associated to Tr for the analysed catchment. Python and Matlab functions to estimate Tr using DMCA-based method are available at https://github.com/giuliagiani/Tr_DMCA, last access 11.09.2020.

Previous application of steps I to IV in economics aimed to understand if two variables were correlated at short, medium or long time scales. The window length L of maximum absolute correlation between the two variables provided an estimate of this time scale (Kristoufek, 2015). We instead reinterpret the results to get a numeric estimate of Tr as half the window length $L_{\min}$-1. Therefore, a further novelty of this work is that we are reinterpreting the output of the DMCA method, as well as applying it in a hydrological context for the first time.

The methodology is a time series analysis technique but does not necessarily require continuous records for robust Tr estimates. When missing values occur in the time series, the methodology will automatically estimate Tr using other periods of the record, hence reducing manual data pre-processing tasks. This is not valid if the data are highly intermittent (e.g. one hourly timestep missing every day) as, by breaking the time series too many times, the Tr estimate can be affected. For a robust Tr estimate the time series should include at least one section with no missing time steps longer than the longest moving average window length L tested.

2.1.2 Interpretation of DMCA-based methodology

This section explains the reasoning for steps I-IV above, and gives an explanation of how the window giving the minimum value of cross-correlation is related to Tr. To follow the explanation of the four steps, we refer to the first column of Figure 1 (Figures 1a-1c), where we graphically represent the steps for a single window length (L=151). The DMCA-based method has been applied to rainfall-streamflow time series but for simplicity in Figure 1 we zoom on an individual event so we can graphically explain in detail the meaning of the steps.

I. A new input will cause a sudden steepening in the cumulative time series (see comparison between Figures 1a-1b (solid lines)). In particular:

- For the cumulative rainfall time series, increases in cumulative rain correspond to new rainfall contributions while flat sections correspond to periods of zero rainfall (solid green line in Figure 1b).
- For the cumulative streamflow time series, we can observe steeper increases in cumulative flow for the rising limb (new streamflow contribution) and flatter increases for recessions (solid grey line in Figure 1b).

II. The moving average (dashed lines in Figure 1b) of the cumulative time series intersects the step change in its centre of mass at the window length scale, generating negative fluctuations (moving average series above cumulative time series) at the beginning of the contribution and positive fluctuations (moving average series below cumulative time series) at the end (see comparison between solid and dashed lines in Figure 1b).
The points where fluctuations change from negative to positive (large dots in Figure 1b) are physically meaningful: they correspond to the centre of mass of the contribution at the window length scale, which refers to centre of mass of rainfall and streamflow. For each rainfall-streamflow event the time interval between these two points can then be interpreted as Tr. One definition of Tr by McCuen (2009) is the time from the maximum rainfall intensity to the peak of discharge. For multi-peak events the maximum intensity/peak does not always provide sufficient information, hence we prefer the use of centres of mass. However, the next steps (III and IV) are required to estimate Tr, as knowing only the position of the centres of mass for each event would imply an independent estimate of Tr for each of them.
At this stage for Equations 3 and 4 the sign of the fluctuations is not important as the fluctuations are squared. These two equations serve only as a measure of the magnitude of fluctuations, which will be used later to normalise bivariate fluctuations.

III. Bivariate fluctuations (the product of rainfall and streamflow fluctuations) determine the sign of the DMCA-based correlation coefficient (Eq.8) as in the numerator (Eq.7) the sign of rainfall and streamflow fluctuations plays an important role.
If streamflow would react instantaneously to rainfall and keep the same frequency spectrum, rainfall and streamflow at any time t would have the same fluctuation sign, i.e. both negative before the centre of mass and positive after it, resulting in positive bivariate fluctuations. Instead, every time a rainfall contribution occurs, streamflow responds with a certain delay and the signal is smoothed out. Therefore, when rainfall fluctuations are already positive because the rainfall centre of mass has passed, streamflow still shows negative fluctuations (it has not yet reached the streamflow centre of mass), causing negative bivariate fluctuations.
Fig 1.c shows fluctuations of the individual rainfall and streamflow signals. The red arrow underlines the time period in which bivariate fluctuations are negative.

IV. Bivariate fluctuations are then normalized by the product of the rainfall and streamflow fluctuations so that the correlation does not depend on the magnitude of the signals.

In Figures 1d-1i we can see the effects of different moving average window lengths, L. Firstly, we can see that fluctuation amplitudes and durations increase with increasing moving average window lengths (Figures 1c, 1f and 1i), as a longer moving average window lengths tend to smooth out more features of the original time series, generating bigger fluctuations.

Given that bivariate fluctuations are negative when streamflow is first responding, bivariate fluctuations are maximized, producing a minimum in the DMCA-based correlation coefficient, when both rainfall positive fluctuations and streamflow negative fluctuations are covering the whole time span between the two centres of mass (between the two dots). This happens only when using a moving-average window length which is double the time between the two centres of mass, i.e. double the Tr (Figure 1e-1f). The factor two in the relationship between Tr and window length is inherent to the centred moving average process, as to generate a fluctuation of one sign for a specific duration, the window length has to be twice as large. Note that the DMCA-based correlation coefficient value does not have a statistical significance level because it is dependent on how many events occurred and on their duration. However, when applying different moving-average window lengths to the same two time series, the value of the DMCA-based correlation coefficient is able to guide us through the estimation of Tr (Figure 1j).

Shorter window lengths (e.g. L=151, Figure 1c) generate negative bivariate fluctuations for a time period shorter than the time span between the two centres of mass (red arrow shorter than the time span between the dots). The DMCA-based correlation coefficient ρ_{DMCA} for a window L of 151 is in fact smaller in absolute terms than the one for a window length of 273 (Figure 1j). Longer window lengths (L=351, Figure 1i), despite covering the entire time span between the centres of mass (time span between the two dots), also produce a significant portion of positive fluctuations (blue arrows). These positive fluctuations increase bivariate fluctuations that, when normalised, result in a smaller in absolute terms value of DMCA-based correlation coefficient (Figure 1j).

In Figure 1f we can see that before the rainfall centre of mass we also have a small portion of positive bivariate fluctuations, but these are smaller than the loss of negative bivariate fluctuations using a smaller window (e.g. L=271), so L=273 is the optimum. In this sense, Tr estimates calculated with the DMCA-based method can suffer from small errors due to the geometry of the integrated time series, but these are minimal and, when the data resolution is adequate, smaller than the range of variability of Tr in an individual catchment.

If we think of negative fluctuations as rising limbs and positive fluctuations as recessions, the moving-average window length associated with Tr is the one which is able to group together rainfall contributions so that the rainfall “recession” is concurrent with the rising limb of streamflow (see Figure 1f). It is equivalent to creating two triangular shapes in which the second half of the rainfall triangle basis overlaps with first half of the streamflow triangle (i.e. recession of rainfall overlapping with rising limb of streamflow).

Figure 1: a-i) Graphic representation of steps (I, II, III) of DMCA-based methodology for moving average window lengths L=151, L=273, L=351. Green lines relate to rainfall, grey lines to streamflow. The red (blue) arrows underline periods of negative (positive) bivariate fluctuations. j) DMCA-based correlation coefficient variability with L, with circles showing correlation for the three window lengths above.

2.1.3 Event scale application of DMCA-based methodology

The DMCA-based methodology has not been built to work on an event-basis but with a few adjustments it is also able to produce estimates for individual events. This is of interest for comparison with existing event-based methods.

If rainfall-runoff events have been selected (see Supporting Information), then for each individual event we create two time series, one concatenating copies of the rainfall event, the other concatenating copies of the related streamflow event. By creating these artificial records we are able to use the method also at the event scale. The copies must be separated with an array of constant values of the same length for both time series and longer than the longest window amplitude tested. In this way, any rainfall contribution occurring after the discharge peak will still be associated with its own copy and not with the following replicated events.

Rainfall events are separated by an array of zero values, whilst the constant value used to separate streamflow events is the last value of the streamflow event. However, it is possible that the beginning and the end of the streamflow event assume different values. When we concatenate the streamflow copies, this can generate step changes, which can alter the estimate of the response time. For this reason, when using the DMCA-based method at event scale, we take into account only those estimates of response time coming from events where the difference between the streamflow value at the beginning and at the end of the streamflow event is less than 10% of the magnitude of the peak.

2.2. Traditional method

Among the multiple definitions available in the literature, the one traditionally used to directly estimate Tr from rainfall and streamflow time series defines Tr as the time from the end of rainfall excess to the inflection point of the total storm hydrograph (McCuen, 2009). This definition of course refers to an individual event. Despite its conceptual simplicity, estimating the end of rainfall excess and the inflection points in the total storm hydrograph and direct runoff can be very challenging (Grimaldi et al.,2012).

The first step is to estimate the volume of direct runoff by separating the hydrograph into baseflow and direct runoff using a recursive digital filter (e.g. Lyne & Hollick, 1979; Nathan & McMahon, 1990):

$$Q_d(t) = \beta Q_d(t-1) + \frac{1+\beta}{2}\left[Q(t) - Q(t-1)\right] \quad \text{(Eq.9)}$$

Where $Q(t)$ and $Q(t\text{-}1)$ are total storm streamflow at times t and t-1, $Q_d(t)$ and $Q_d(t\text{-}1)$ are direct streamflow at times t and t-1 and β is the recursive filter parameter.

The filter is applied three times (forward-backward-forward) to minimize the shift in time of the output caused by the filtering process (Nathan & McMahon, 1990). The parameter β is estimated so that the baseflow hydrograph passes through the inflection point of the total storm hydrograph.

Many alternative methods are available for baseflow separation but they all suffer from significant uncertainties, as they involve parameter estimations which do not have an independent physical meaning (e.g. Sloto & Crouse, 1996; Lyne & Hollick, 1979; Furey & Gupta, 2001; Eckhardt, 2005). Unless experiments with tracers or groundwater measurements have been conducted in the examined catchment, the absence of a "true" baseflow makes the objective evaluation of the different methods impossible (Eckhardt, 2008).

The end of rainfall excess is computed using the Soil Conservation Service Curve Number (SCS-CN) method (USDA-SCS, 1986; Chow et al., 1988) in which the CN (Curve Number) is estimated by assuming that the volume of excess rainfall is equal to the volume of direct runoff. However, this methodology can sometimes lead to unrealistic estimates of Tr: this is the case when close to the end of a rainfall event rainfall is falling at very low intensity. Because of the previous rainfall which presumably saturated the soil, this low intensity rainfall falling just after is considered excess rainfall moving forward in time to the end of the rainfall excess. This leads to very short Tr estimates, which in some cases can even become negative (Figure 2). More specifically, when using the traditional method in this paper, a rainfall event was discarded if the total rainfall in the last three hours of the event was smaller than three times the average rainfall rate for the whole event, or less.

Figure 2: Example of an event (catchment ID: 41025) which has been discarded due to the long tail in the rainfall record (crosses represent end of rainfall excess (top) and inflection point in the hydrograph (bottom)).

2.3. Lag estimate from Flood Estimation Handbook

In this work we used an estimate of response time retrieved from catchment descriptors to guide the event selection (see Supporting Information) and to discuss any large difference between Tr estimates from DMCA-based method and traditional method. Although rainfall and streamflow records are available, the idea is to calculate an estimate of response time which is independent from any direct observation from the data, using established methods.

In particular, in the Flood Estimation Handbook (FEH - Snyder, 1938; Houghton-Carr, 2008) the lag is defined as the time from the centroid of total rainfall to the runoff peak or centroid of runoff peaks. This definition is similar to the ones adopted by the other methods applied in this work to describe Tr. However, this is not surprising as McCuen (2009) highlighted that there is sometimes overlap in the definition of Tr and time lag.

Taking information from the FEH (Houghton-Carr, 2008), we estimate time to peak T_{p0} using catchment descriptors (Equation 10) and then from the time to peak we derive the lag (LAG) using an empirical formula (Equation 11). These empirical relationships are valid for UK catchments only:

$$T_{p0} = 1.684\, DPSBAR^{-0.18} PROPWET^{-1.05} DPLBAR^{0.48} (1 + URBEXT)^{-4.39}\ [\text{h}] \quad \text{(Eq. 10)}$$

$$LAG = \left(\frac{T_{p0}}{0.879}\right)^{1.05} [\text{h}] \quad \text{(Eq. 11)}$$

Where DPSBAR is the Drainage Path Slope [m km^{-1}], PROPWET is the proportion of time soils are wet [-], DPLBAR characterizes catchment size and configuration [km] and URBEXT is the urban extent [-]. For all the catchments for which the descriptors were available, lag estimates are reported in Table S1.

3. Study catchments and data

We compare the DMCA-based method with the traditional method in a subset of catchments from the UK's National River Flow Archive (NRFA). We use catchments from the UK Benchmark Network 2 (UKBN2) which have been classified as near-natural (Harrigan et al.,2018). We will make use of this set of near-natural catchments to test the proposed methodology without adding more complexity due to human disturbance.

Mean areal hourly rainfall has been derived from the continuous CEH-GEAR1hr dataset for each catchment (Lewis et al., 2018). Streamflow data at 15-min step were provided by the Environmental Agency (EA), Natural Resources Wales (NWR) and Scottish Environmental Protection Agency (SEPA) and then processed to obtain hourly streamflow time series. The percentage of missing values in the available streamflow records varies from 0 to 60% with a median value of 0.2%. We did not discard the catchments with higher percentages of missing values as the other parts of the records were long enough to compute reliable estimates of Tr.

Rainfall and streamflow time series at hourly resolution were available for only 113 out of 146 catchments. Base Flow Index (BFI) is provided for catchments in the UKBN2, and to guarantee a fast hydrograph response we excluded catchments with very large BFI (> 0.85). This reduced the catchment study set to 98 of the 146 catchments of UKBN2 (see Figure 3, all markers), with areas ranging from 8 to 1508 km^2. For these catchments, the record length for which both hourly rainfall and streamflow data are available varies from 17 to 24 years.

Since the traditional method can only be used on an event basis, we need to select individual rainfall-streamflow events from the continuous time series. To do so, we used the methodology outlined in Supporting Information which involves the use of catchment descriptors. Taking information from the UK hydrometric Register (Marsh & Hannaford, 2008) and Flood Estimation Handbook (FEH) (Bayliss, 2008), the descriptors were only available in 79 of the 98 basins. However only for 76 catchments, it was possible to find a set of events which were suitable for the application both of DMCA method and traditional method. Therefore, the evaluation of DMCA method against the traditional method (Sections 4.1 and 4.2 and Figures 4) is further restricted to just these 76 catchments (Figure 3, see catchments represented with a blue asterisks), while the robustness analysis of DMCA (Section 4.3 and Figures 6) is performed on the 98 catchments (Figure 3, see all catchments) as no event selection is needed.

Figure 3: Locations of the 98 study catchment outlets with their National River Flow Archive identification number (orange circles show catchments used only for robustness analysis (Section 4.3), blue asterisks show catchments used both for evaluation (Sections 4.1,4.2) and robustness analysis (Section 4.3)).

4.Results

4.1. Event-based comparison: does the median value of the Tr distribution with DMCA-based methodology match the median from the traditional method?

As mentioned in the methodology section, both the DMCA-based method at event scale and the traditional method are unable to provide reliable estimates of Tr for some types of events. Hence, we introduced a discarding rule for each method. After selecting the rainfall-streamflow events (see Supporting Information), we compared the two methodologies in each catchment considering only the events for which both Tr estimates were available. As a result, in each catchment we produced two Tr sample distributions, one for each method, based on the same set of events.

The number of events for which Tr estimates are available with both methodologies ranges from 1 to 183 events with a median value of 21 events across the different catchments. These numbers come from the intersection of the Tr estimates from the traditional method (number of events ranges from 5 to 685 with a median of 63 events) and the estimates from the DMCA-based methodology at event scale (number of events ranges from 27 to 816 with a median of 178 events).

In Figure 4a we compare Tr estimates from the DMCA-based method and traditional method performed on an event basis. Each catchment is represented by a circle showing the median Tr estimate when using both methodologies across all of the considered events, with the bars then highlighting the 25th and 75th percentiles. Blue and red colours stand respectively for sample larger/equal and smaller than 10 events, as small samples of events might lead to less robust estimate of Tr.

Overall, we can see that the median values (circles in Figure 4a) of the two Tr distributions derived with two methodologies are mostly on a 1:1 line (Spearman rank correlation equal to 0.82). This indicates that DMCA-based method produces results which are generally similar to the traditional method.

4.2. When using DMCA-based methodology, does the Tr estimate from the analysis of the entire time series match the median of the estimates from individual events?

In the previous section we used the DMCA-based methodology for individual events and the results were compared with the traditional method. However, as mentioned in the methodology section, the DMCA-based method was originally developed to analyse the entire time series and not just on an event basis. The aim is to find an average Tr for the whole record.

Hence, we applied the DMCA method for estimating on both an event basis and across the entire rainfall and streamflow time series. We compared the Tr estimate from across the entire time series to the median Tr estimate of the individual events (Figure 4b). We use color-coding to distinguish those catchments whose median is based on an event sample smaller or larger than 10 events.

The median value of the Tr distribution using DMCA-based methodology for individual events compares well with the Tr estimate on the entire time series (Spearman rank correlation equal to 0.94), showing that the process of event identification is not needed when using the DMCA-based method.

Figure 4: a) Median, 25th and 75th percentiles of times of concentration distributions for each catchment using the traditional method and the DMCA-based method. Capital letters refers to catchments mentioned in the Section 5.1. b) Comparison of application of DMCA-based methodology on the entire time series with median of Tr distributions of individual events. In

both plots catchments in red (blue) highlights catchments where less than (more than or equal to) 10 independent events were identified. Note logarithmic scales.

4.3. How sensitive is the DMCA-based methodology to the length of the record and to noise and bias in the time series?

As a first test, we evaluate the robustness of our proposed methodology for shorter records. In each catchment we break down the original time series in two calendar year sub-dataset and for each of them we computed the Tr using the DMCA-methodology (e.g. for an original rainfall-streamflow record from 1990 to 2010, the two-calendar-year sub-datasets are 1999-2000, 2000-2001, …, 2009-2010). In Figure 5a we show with a blue bar the minimum-maximum range of Tr estimates obtained with all the two-year datasets in each of the 98 catchments. The star represents the Tr using the whole available record length, which ranges from 17 to 24 years in different catchments. We repeated the same procedure for sub-datasets of 5 and 10 years (Figure 5b and 5c).

The results show that the DMCA-based methodology can produce robust estimates even with relatively short rainfall-streamflow records. Figure 5a shows that for catchments responding in less than 10 hours a two-year record of hourly data is already long enough to robustly estimate Tr, as shown by the minimum and maximum values converging towards the estimate from analysing the time series as a whole. Catchments responding in 10-20 hours require longer time series with at least 5 years of hourly data. In catchments where the response time is greater than 20 hours, at least 10 years of hourly data are needed for robust estimates. Therefore, according to our DCMA methodology, the record length of hourly data needed for robust Tr estimation increases with increasing response times of the catchment.

Figure 5: Tr estimates using subsets of 2(a), 5(b), 10(c) years (blue bars). The triangle represents the Tr estimate using the entire record. Where no bar is visible, the range of estimates was smaller than the width of symbol.

Our second test evaluates the robustness of the methodology when time series are affected by noise. We add random Gaussian noise to rainfall and streamflow time series with standard deviations of 5% and 25% of the mean value, respectively green stars and orange circles in Figure 6a. This means that 98% of the data points increase or decrease their values by 0-10% of the mean value, when the standard deviation is equal to 5% of the mean, and by 0-50% of the mean when the standard deviation is 25% of the mean. We then compare Tr estimates from the perturbed and original time series (respectively green stars/orange circles and black triangles in Figure 6a), applying the DMCA method across the entire length of each of the records.

Results show that adding noise to the original streamflow record has a minimal effect on the Tr estimates computed with the DMCA-based methodology. Only 4 out 98 catchments show variations in Tr estimate when Gaussian noise with standard deviation of 5% of the mean is added to the original rainfall and streamflow time series (green stars in Figure 6a). The average error is less than 1%. When the standard deviation of the Gaussian noise increases to 25% of the mean value, 33 catchments are affected (orange circles in Figure 6a), with an average error of 10%.

As a further test, we also add bias equal to the mean value to both rainfall and streamflow time series to represent time series affected by systematic bias. If a time series does not have any missing values, adding bias does not generate any variation in the Tr estimate. Missing values in the time series produce discontinuities in the moving averaging process which might lead to small errors. Adding bias equal to the mean value only affected Tr estimates from 6 out of 98 catchments, with an average error of less than 2% (Figure 6b). With this test we show that if additional bias does not significantly alter the shape of the cumulative time series (i.e. the bias is systematic), its effect on Tr estimates is minimal. If the bias is non-systematic its magnitude has still to be big enough to move significantly the centres of mass at window scale to generate any difference in the Tr estimate.

Figure 6: a) Tr estimates using the original time series (black triangles), and adding Gaussian noise with standard deviation equal to 5% the mean value (green stars), or with standard deviation equal to 25% the mean value (orange circles). Often the three markers overlap meaning that there is not difference among the three estimates. b) Tr estimates using the original time series (black triangles), and systematic bias equal to the mean time series value with standard deviation (magenta circles).

5.Discussion

5.1. Comparison between the DMCA-based and traditional method.

Event based estimates of Tr from the proposed DCMA methodology are similar to those found from the traditional method. There are only two catchments which show significant differences in the median Tr values using the two methodologies (see catchment labelled with A (NRFA ID: 40011) and B (NRFA ID: 54008) in Figure 4a). From manually inspecting the events on which the estimates have been produced, the DMCA-based methodology seems to give more realistic estimates. This is also confirmed by the similarity of the DMCA-based estimates with the lag estimates computed for those catchments using the FEH guidelines (Bayliss, 2008; Houghton-Carr, 2008) (see Supporting Information, Table S1). In fact, for catchment A, the lag estimate according to FEH guidelines is around 14 hours (19 hours for DMCA and 2 hours using the traditional method) while for catchment B is around 16 hours (17 hours for DMCA-based and 6 hours using the traditional method). The similarity between Tr estimates with DCMA-based method and lag estimates using FEH guidelines suggests DMCA-based estimates are more likely reliable than that obtained from the traditional method in these sites.

The reason why the traditional method performs worse in those catchments is related to the definition upon which the method is built. As pointed out by McCuen (2009), the end of rainfall excess and the inflection point in the hydrograph are both based on individual features and uncertainty in their estimates is generally higher than for average values. Consequently, when the sample is relatively small, this uncertainty can affect the median value. The DMCA-based methodology has the advantage of computing Tr considering the centre of mass of rainfall and streamflow at the scale of the moving average window.

When looking at the 25^{th} and 75^{th} percentiles of the distributions we can clearly see that both methods find variability in the Tr estimate across different events. This is not surprising as many studies suggested that the response time of a catchment is a function of the excess rainfall or rainfall intensity (Michailidi et al., 2018; Kjeldsen et al., 2016; Izzard, 1946; Morgali & Linsey, 1965; Askew, 1970; Papadakis & Kazan, 1987; Loukas & Quick, 1996). However, ranges of variability coming from the two methods seem to be visually comparable for most of the catchments, meaning that not only the median values but also the distributions are similar. When ranges for the traditional method are wider it is usually because the method is based on the estimates of extreme features in the hyetograph and hydrograph (e.g. catchment C (NRFA ID: 11004) in Figure 4a). Because the Tr estimates from DMCA-based method are based on centres of mass and hence more stable, we suggest that larger ranges in DMCA-based distribution are instead representative of the actual variability. In fact, unlike the traditional method which searches for the inflection point within a time window following the end of the rainfall, the DMCA-based method is free to search for the actual response having effectively no constraints. The maximum window length tested is set far larger than the expected time scale and therefore this method could cope also with more "unexpected" responses (e.g. catchment D (NRFA ID: 37005) in Figure 4a).

One of the main advantages of using the DMCA-based method compared to the traditional method and the other methods summarized by McCuen (2009) is that it avoids the highly uncertain hydrograph separation (Eckhardt, 2008). The Tr estimates from the traditional method and other methods summarized by McCuen (2009) are dependent on the choices made at the baseflow separation stage, while the DMCA-based method is more objective as it does not require any user decision.

Another significant advantage of using the DMCA-based methodology is that it does not make any assumption about the rainfall-runoff transformation unlike the currently used methodologies (e.g. the traditional method assumes that the volume of direct runoff is equal to the volume of excess rainfall in the associated hyetograph). Recent results from tracer studies (e.g. McDonnell, 1990; Berghuijs & Allen, 2019; Gallart et al., 2020) have also shown weaknesses about our understanding of rainfall-runoff transformation, so in this sense, the DMCA-based methodology could be an effective tool to estimate the response of the catchment even when assuming that the precipitation which is building the hydrograph is not only the precipitation fallen during the last rainfall event.

5.2. DMCA-based method at event scale and on continuous time series.

Despite the general good agreement between median estimate from individual events and the estimate using the entire time series, it seems that the median value of the individual events lead to larger response times compared to the full time series analysis (Figure 4b). The reason might be that the Tr estimate on full time series gives more weight to bigger floods as they generate a larger portion of negative bivariate fluctuations. In fact, bigger floods seem to show smaller Tr, as the median Spearman rank correlation value between magnitude of the peak and Tr across the 76 catchments is equal to -0.54. This relationship is supported by many studies which show that the response time of a catchment decreases with increasing rainfall or effective rainfall intensity (Michailidi et al., 2018; Kjeldsen et al., 2016; Izzard, 1946; Morgali & Linsey, 1965; Askew, 1970; Papadakis & Kazan, 1987; Loukas and Quick, 1996). As a result, the Tr estimates from DMCA-based method applied to entire time series cannot be considered an upper limit of the time needed to respond, as intended by the glossary definition (W.M.O., 1974; Johansson, 1984), but it could be particularly useful for engineering applications where usually bigger floods are the ones of interest.

It is important to note that by applying the methodology to the time series we avoid the event selection step, which is not standardized (Merz & Blöschl, 2009; Tarasova et al., 2018; Mei & Anagnostou, 2015), and is recognized to affect the statistics at the event scale (Dunkerley, 2008). Unlike the traditional method, the DMCA-based methodology applied to the full time series, not only avoids the baseflow separation but also removes the uncertainty around the event selection step by processing the entire time series at once. Therefore, the method can be considered as more objective, since it removes the three biggest sources of uncertainty arising from the application of the methods summarized by McCuen (2009) listed in the introduction section (selection of events, baseflow separation, estimate of hyetograph/hydrograph characteristics).

For the reasons explained in the paragraph above and because the method considers a large number and types of events though the use of the entire record, the DMCA-based methodology could be useful for a robust calibration of empirical formulae. Instead, methods summarized by McCuen (2009), which require an event-by-event procedure, could make difficult to consider a significant number of events which also show a variety of different characteristics (Grimaldi et al., 2012; Gericke & Smithers, 2014).

5.3. Robustness analysis of DMCA-based method.

By breaking down time series in sub-datasets of 2, 5 and 10 years (Figure 5), we find that catchments with quicker response times require shorter record lengths for reliable Tr estimate. The reason might be very simple: when a catchment is slow in responding, over a given time period we are able to observe fewer events in comparison to catchments with quicker response times. Although the methodology works on the whole record, the sections of the records important for the Tr estimate are the ones when the streamflow is responding to the rainfall. Therefore if you consider an equal record length in catchments which respond both quickly and slowly to rainfall, in a slow responding catchment these sections are fewer than in a faster responding one because the slow catchment tends to cumulate more rainfall over time in a single response.

From this analysis we can conclude that, unless the record is too short compared to the average response time of the catchment, the DMCA-based method is not sensitive to sample size effects as minimum-maximum Tr ranges computed with different n-year sub-datasets are quite narrow. The lengths of the records examined herein can be considered fairly short. Therefore, the method can probably be successfully applied also in catchments for which long records are not available. However, the above conclusion could change in different climates. For example, in arid climates the frequency of the events could be so low that we might need a very long record for a robust estimate of Tr. Therefore, we can consider the results about robustness to short record valid for wet climates only and further testing will be needed in other climatic regions.

Furthermore, we show that the proposed method for estimating Tr is robust to noise (Figure 6a) and systematic bias (Figure 6b) within the time series. This means that we could apply this methodology even if rain gauge data are not available and we need to make use for example of radar rainfall estimates. Radar rainfall estimates, due to the process of retrieving rainfall intensities from a signal, are more susceptible to noise and bias (Fabry, 2015). These are usually corrected using specific algorithms (e.g. Chumchean et al., 2006) but there might be still some residual errors. However, with the noise and bias tests we showed that Tr estimates using the DMCA-based method would be only minimally affected by slightly inaccurate time series.

Overall, the DMCA-based methodology is demonstrated to be robust with respect to relatively short records and presence of artificial noise and bias. For the traditional method a similar analysis could be performed only on an event basis, hence the results would be strongly affected by the decision made at event selection, separation of the hydrograph and estimation of features stages. Therefore, it would be difficult to assess the actual impact of noise and bias because algorithms would require adjustments (e.g. when looking at noisy time series, we would probably need to apply a strong smoothing function to the streamflow time series to find the inflection point in the hydrograph).

6.Summary

Current methodologies to estimate Tr from observed hyetograph and hydrograph show weaknesses in their assumptions and require uncertain and subjective steps. Therefore, we recommend the use of the DMCA-based methodology to estimate the Tr (Python and Matlab code available at https://github.com/giuliagiani/Tr_DMCA, last access 11.09.2020). This method removes many of the sources of uncertainty which affect the existing methods. The DMCA method makes no hypothesis about the rainfall-runoff transformation, avoiding also the uncertain step of hydrograph separation. Furthermore, no selection of rainfall-streamflow events or any parameter estimation are required.

The proposed methodology produces estimates of response time that match the ones from the traditional method, showing that the time scale retrieved can be treated as Tr. When applied to the entire time series at once (the intended application) the DMCA-based methodology is easily reproducible as it does not require any user decision. We also show the method is robust to relatively short record lengths, artificial noise and bias within the time series. It is important to note that the DMCA method fully relies on the quality of the data and processing the entire time series at once makes it more difficult to spot anomalous records (although the influence of an individual event is limited, if we have a sample of many events). Hence, it is important that data are quality checked, especially for timing errors. Moreover, another limitation of this method (as many others) is that the proposed method does not provide a physical explanation of the retrieved time parameter.

In this paper we have shown the application of the DMCA-based methodology to estimate Tr using hourly time series. This could be particularly useful for a more robust calibration of empirical formulae and for other engineering applications such as designing hydrographs for assigned return periods. Note that our method does not conflict with the hypothesis that hydrographs may incorporate water that fell in previous events. Furthermore, the methodology can be applied at coarser or finer temporal resolutions as long as the temporal resolution of the data is high enough to capture the time delay between the two time series (e.g. no streamflow peak recorded at the same time step of the associated rainfall peak). However, the coarse temporal resolutions may be less informative. For example, in the same set of catchments analysed in this work, daily rainfall and streamflow records would have provided estimates of Tr equal to 1 day for most of the sites, showing that daily data for these predominantly small catchments contains little information on flood event response times.

We also suggest that this methodology might be useful for other applications than the estimation of Tr. As long as the temporal resolution of the data is suitable for capturing the phenomena, the DMCA-based method can be used to estimate the response time of any variable to a system driver (e.g. response time of the Biochemical Oxygen Demand concentration in the water when a new rainfall event occurs, or response time of river flow to a snowmelt event).

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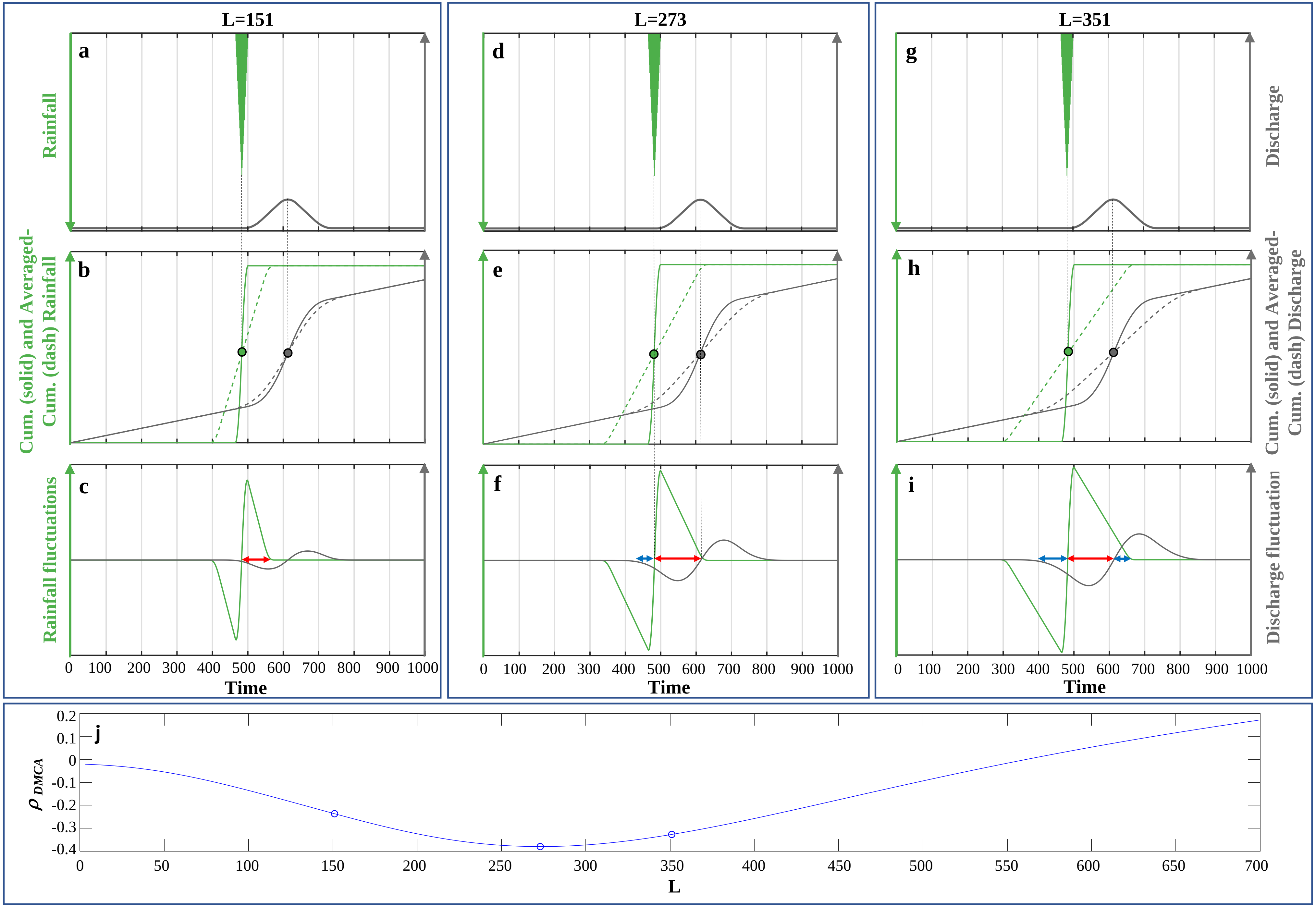
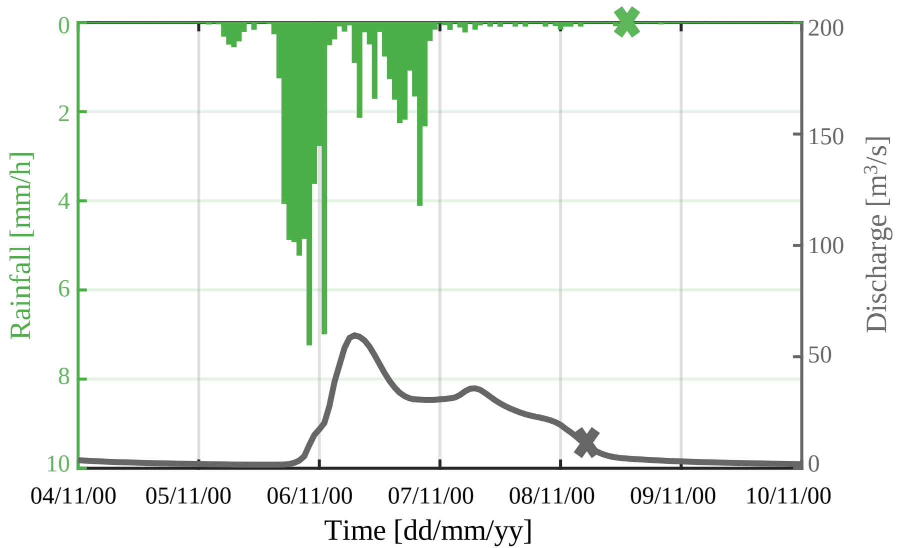
Figure 1.



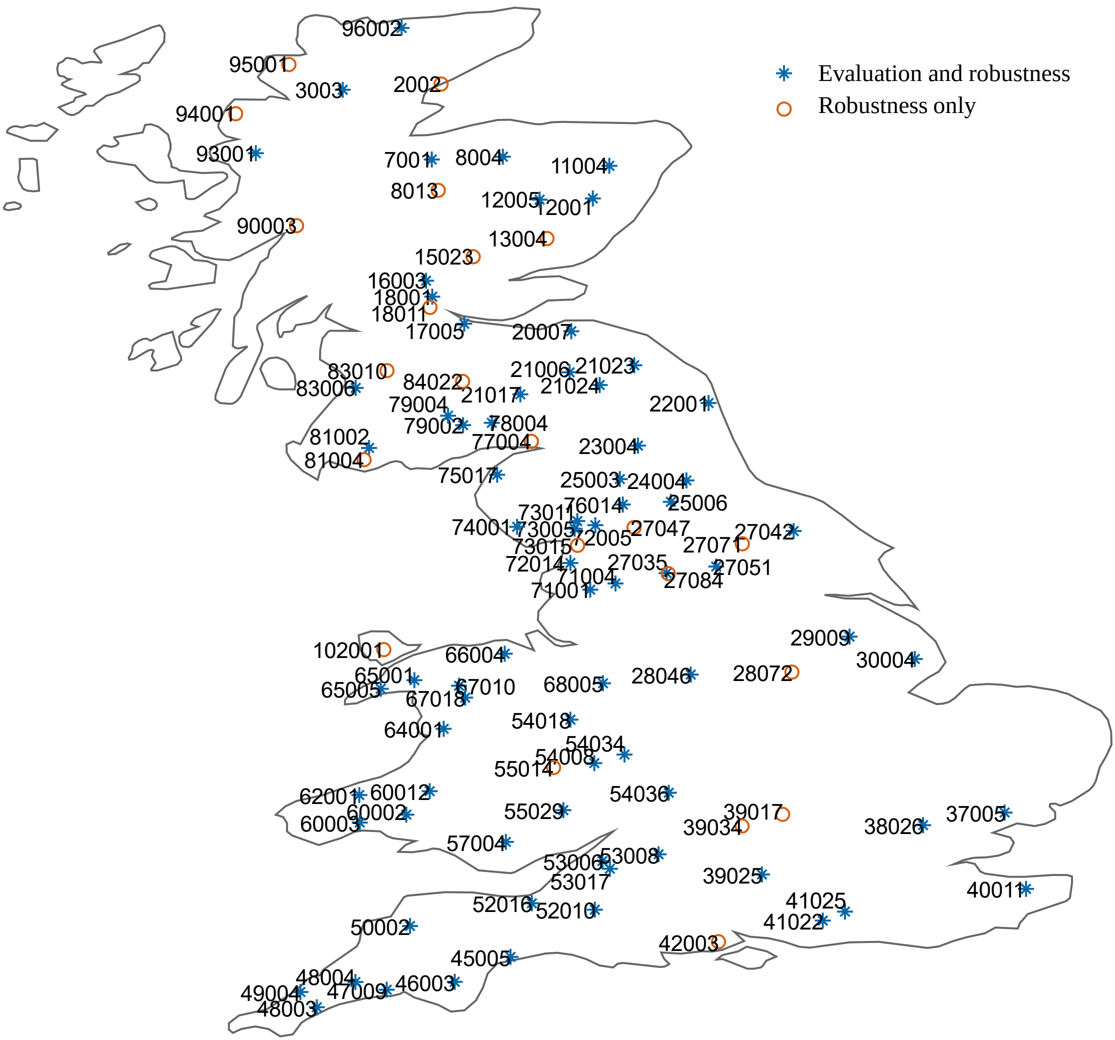
L=151
L=273
L=351
a
b
c
d
e
f
g
h
i
j
Rainfall
Cum. (solid) and Averaged-
Cum. (dash) Rainfall
Rainfall fluctuations
Discharge
Cum. (solid) and Averaged-
Cum. (dash) Discharge
Discharge fluctuation
0 100 200 300 400 500 600 700 800 900 1000
Time
ρ_{DMCA}
0.2 0.1 0 -0.1 -0.2 -0.3 -0.4
0 50 100 150 200 250 300 350 400 450 500 550 600 650 700
L

Figure 2.



Rainfall [mm/h]
0
2
4
6
8
10
Discharge [m^3/s]
200
150
100
50
0
04/11/00
05/11/00
06/11/00
07/11/00
08/11/00
09/11/00
10/11/00
Time [dd/mm/yy]

Figure 3.


Evaluation and robustness
Robustness only
96002
95001
3003
2002
94001
93001
7001
8004
11004
8013
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15023
16003
18001
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62001
60012
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39017
60002
55029
37005
60003
39034
38026
57004
53008
53006
53017
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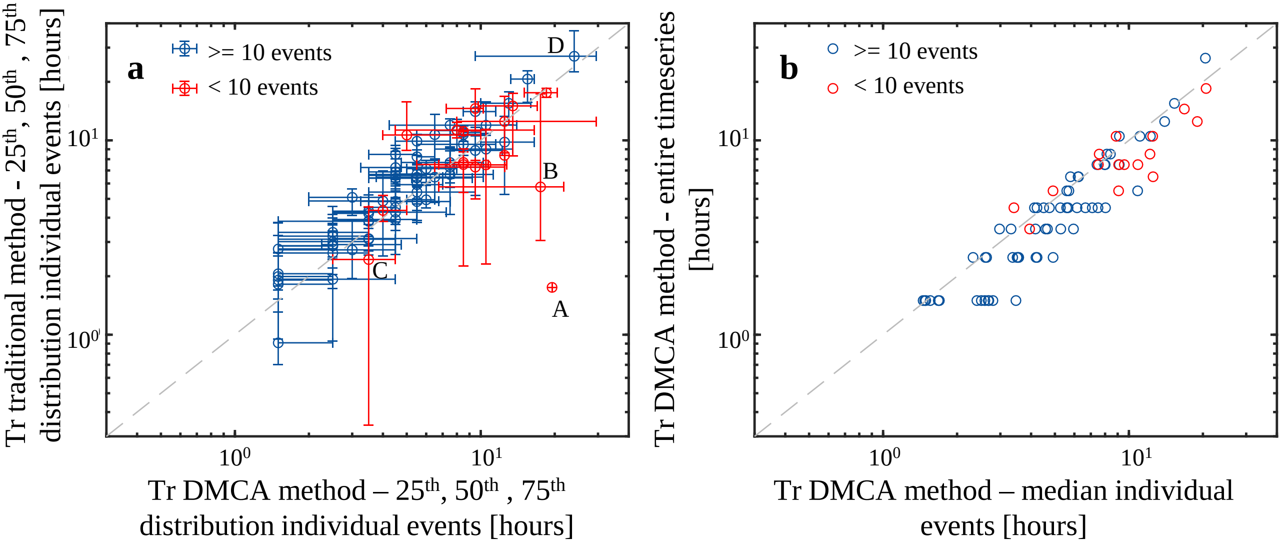
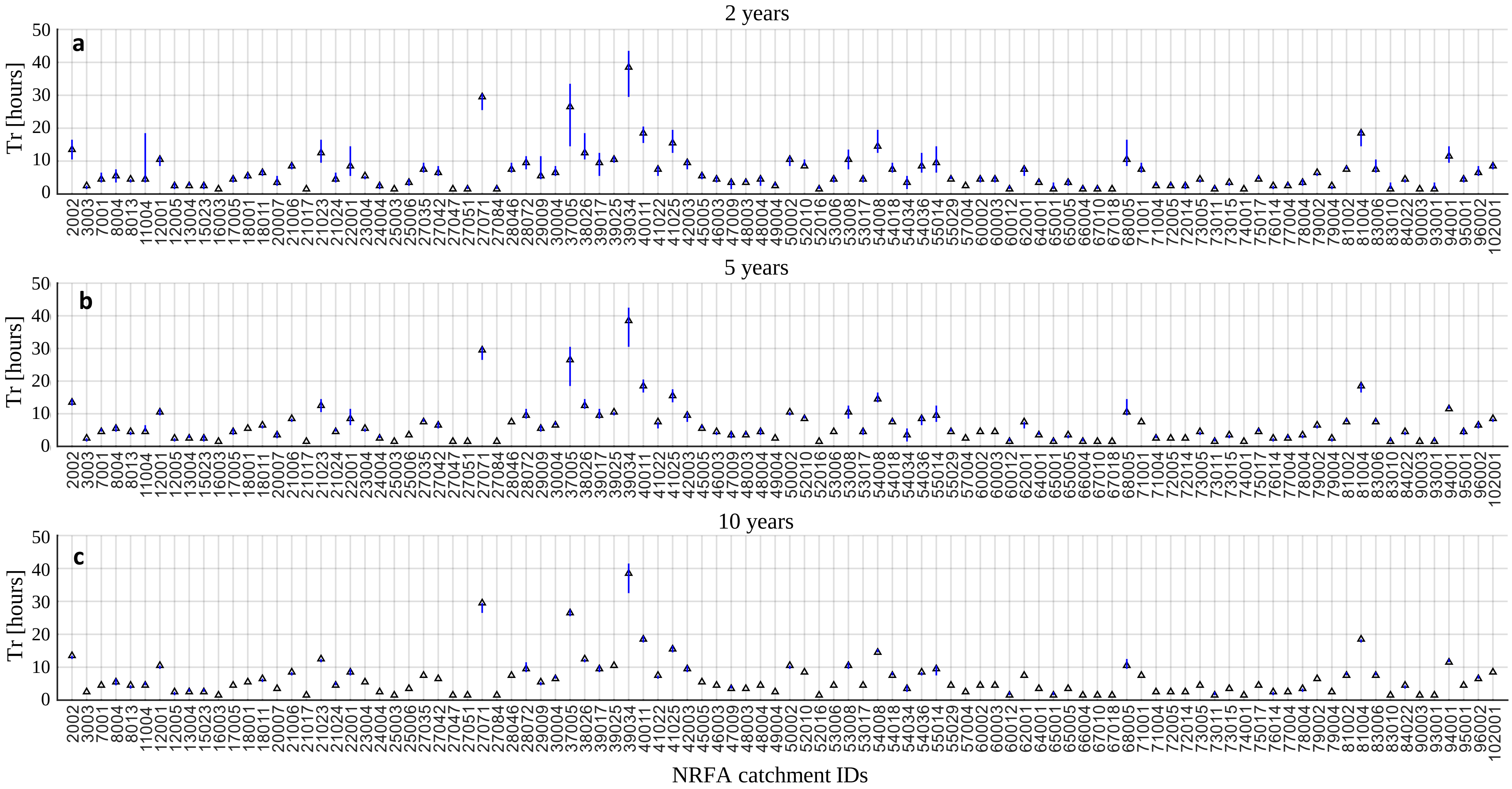
48003

Figure 4.



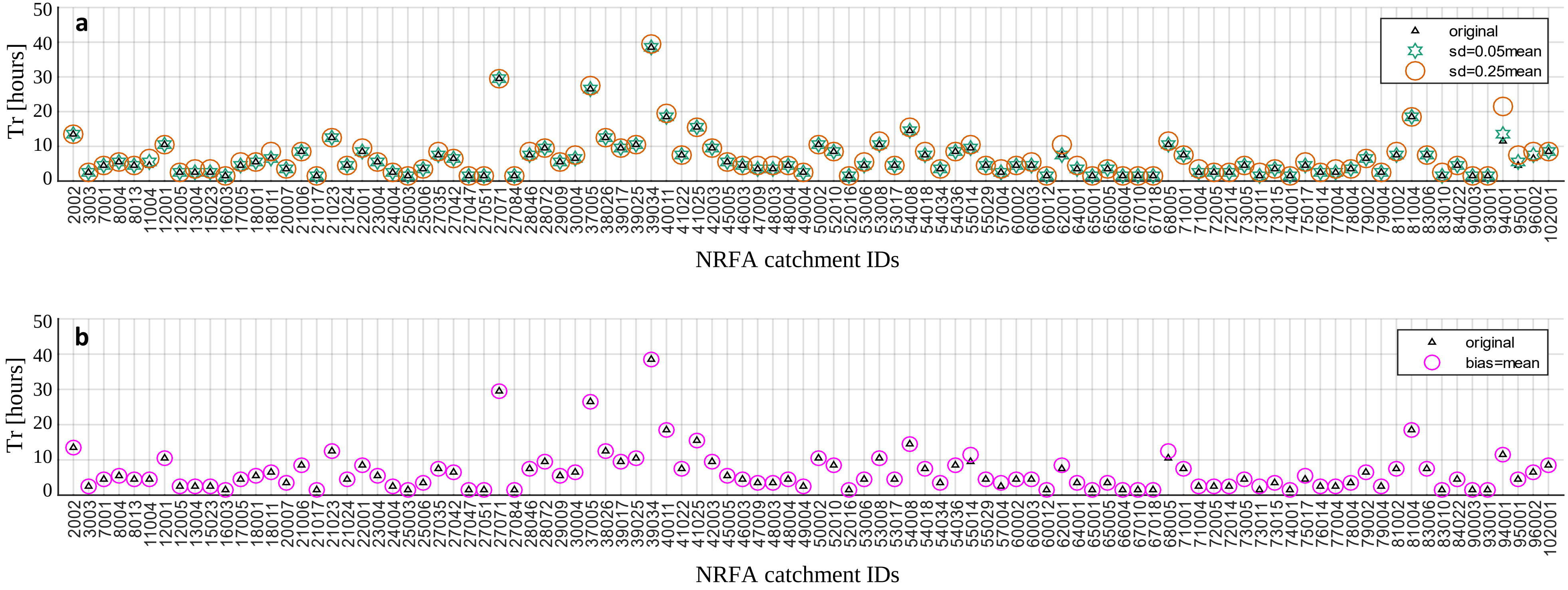
a
>= 10 events
< 10 events
D
B
C
A
10^1
10^0
Tr traditional method - 25th, 50th, 75th distribution individual events [hours]
Tr DMCA method – 25th, 50th, 75th distribution individual events [hours]
b
>= 10 events
< 10 events
Tr DMCA method - entire timeseries [hours]
Tr DMCA method – median individual events [hours]

Figure 5.



2 years
5 years
10 years
a
b
c
Tr [hours]
NRFA catchment IDs

Figure 6.


a
b
Tr [hours]
NRFA catchment IDs
original
sd=0.05mean
sd=0.25mean
bias=mean